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Online Practical Deep Learning Education: Using Collective Intelligence from a Resource Sharing Perspective

Binbin Yong[1], Xuetao Jiang[1], Jiayin Lin[2], Geng Sun[3] and Qingguo Zhou[1*]
[1]School of Information Science and Engineering, Lanzhou University, Lanzhou, China // [2]School of Computing and Information Technology, University of Wollongong, Wollongong, NSW, Australia // [3]Vermilion Cloud, Surrey Hills, NSW, Australia // yongbb@lzu.edu.cn // jiangxt18@lzu.edu.cn // jl461@uowmail.edu.au // gs147@uowmail.edu.au // zhouqg@lzu.edu.cn
[*]Corresponding author

ABSTRACT: Deep learning (DL), as the core technology of artificial intelligence (AI), has been extensively researched in the past decades. However, practical DL education needs large marked datasets and computing resources, which is generally not easy for students at school. Therefore, due to training datasets and computing resources restrictions, it is still challenging to popularize DL education in colleges and universities. This paper considers solving this problem by collective intelligence from a resource sharing perspective. In DL, dataset marking and model training both require high workforce and computing power, which may implement through a resource sharing mechanism using collective intelligence. As a test, we have designed a DL education scheme based on collective intelligence under the background of artistic creation to collect teaching materials for DL education. Also, we elaborate on the detailed methods of sharing mechanisms in this article and discuss some related problems to verify this shared learning mechanism.

Keywords: Deep learning education, Datasets and computing resources, Collective intelligence, Resource sharing perspective

1. Introduction

Artificial Intelligence (AI) has attracted the attention of many researchers since the invention of computers. A lot of work has been done to endow machine intelligence. However, only in recent years, with the development of deep learning (DL) technology (Lecun et al., 2015), AI has made significant breakthroughs in theories and applications. It was proved that a multi-layer perceptron (MLP) could simulate any function with a lot of computation for training the MLP model (Pinkus, 1999). The backpropagation (BP) algorithm (Hameed et al., 2016) was then applied to train a shallow neural network model (equal to MLP) in the 1980s when the personal computer (PC) was invented, and the computing power was greatly improved. Then, neural network technologies had remained stagnant until the mid-2000s because of the small samples and low computing power. In fact, the support vector machine (SVM) (Zhi et al., 2018) model was widely studied and used in this period due to its high accuracy for small samples.

With the development of mobile Internet technology, data has shown a trend of explosive growth since the beginning of this century, which has brought the era of big data (Daniel, 2015). One point of big data is that knowledge is no longer a concise statement or a formula. It is indeed stored in massive data. Therefore, a type of model that can learn the internal statistical characteristics of big data is needed.

Meanwhile, the computing performance of computers increases exponentially. Both big data and high computing performance two factors triggered the revolution of DL technologies. According to the law of large numbers, the empirical risk of a forecasting model will tend to be expected risk when the number of training samples tends to be infinite. Therefore, with the advent of big data, more data brings more accurate predictions. On the other hand, according to the basic theory of neural networks, three layers neural network can simulate any functions with enough hidden nodes. In 2012, Krizhevsky et al. (2012) proved deep neural networks' strong patterns recognition performance combined with big data. Later research indicated that a deeper neural network could be fully utilized to mine the data rules and make predictions. A Deeper neural network can bring more substantial capabilities, feature extraction, and feature learning capabilities (Ayinde et al., 2019). Meanwhile, a deeper neural network also needs more computing resources to train, which is still difficult for ordinary college students. Overall, the practical learning of DL is mainly based on two essential conditions: large amounts of training datasets and adequate computing resources.

Nowadays, typical DL applications, such as image recognition (He et al., 2015), speech recognition (Hinton et al., 2012), natural language processing (Tingting & Mengyu, 2019), autonomous vehicle (Ye et al., 2018), and robot (Chao et al., 2019) are widely researched and developed (Lo & Shu, 2005). A decade ago, Welham (2008) discussed the difficulties of using AI in education. The paper showed several issues that slowed down the pace of AI entering the field of education. However, due to the rapid development of DL technologies, the environment has changed a lot. DL technologies have revolutionized research methods in many fields, and it also changed the content of the AI-related education curriculum. In 2019, 35 universities in China were first approved to add AI specialty for undergraduates (China Daily [CD], 2019). AI used to be an elective major at the undergraduate level in China. Current AI courses and textbooks are generally too old to meet teaching needs. Therefore, new materials and procedures containing the latest DL contents need to be developed for undergraduates. As the critical issues in DL, dataset and computation problems (Krizhevsky et al., 2012) for DL practice learning need to be researched for available teaching schemes.

Aimed at sharing Chinese artwork by DL course, we chose Dunhuang data as our material. Dunhuang murals are the representatives of ancient Chinese grotto murals. Although these murals have had a history of thousands of years, they have shown different styles in painting images and color forms. They utilized a small number of colors to paint pictures, which did not make people feel monotonous. In contrast, they show a unique gorgeous. Dunhuang frescoes reflect ancient China's culture and art style, which can be well used for reference by today's art design. Dunhuang's mural images show different characteristics in the various dynasties. They can also be divided into different categories according to their contents, such as flying apsaras, landscape painting, Buddhistic stories, etc.

In this paper, we propose schemes to address these DL education problems by using collective intelligence from a resource sharing perspective. Based on the background of artistic creation, we design a scheme to collect teaching materials for the DL teaching test. Then, we found that the shared approaches taken in the design of the DL course can help address the datasets and computing challenges currently present in DL education. We also did a short DL course practice to test the learning effect. Furthermore, this paper gives the artworks designed and implemented by students in class. Also, evaluation results of the DL course are given according to the questionnaire results. It should be emphasized that we are not providing perfect course schemes that can be applied in any scenario. In fact, we present some feasible approaches in practice for general DL education. Teachers can change the DL course contents based on schemes proposed in this paper and specific teaching environments.

This paper will focus on using a practice perspective to share the datasets and computing resources. We will explore the resource sharing methods, suitable and typical DL course contents, and project practice content. Compared with previous work, our research mainly has the following contributions.

- From a resource sharing perspective, a collective intelligence scheme is designed for DL course materials.
- A concrete sample for using collective intelligence for the DL course is conducted based on the background of art creation.
- Approaches to solving the dataset and computing problems are given and discussed.
- A DL course practice is conducted to verify the DL education effect. And the course practice results and evaluation are given and analyzed.

The rest of this paper is organized as follows. Section 2 analyzes the investigations of current challenges for DL education. In Section 3, we present the coping strategies for these challenges. Section 4 present the contents of the DL course. Section 5 presents the discussion and conclusion of this study.

2. Current challenges

As discussed in the introduction section, the critical challenges in practical DL education mainly focus on the course materials, especially dataset and computation problems, which are rarely discussed in the literature. And there is little research that focuses on this.

2.1. Course challenge

For DL courses, some open courses can be found online, such as MOOC (Freitas et al., 2015; Liyanagunawardena et al., 2015; Terras & Ramsay 2015), Coursera, and Udacity (Giannakos, 2013), etc. These online courses have promoted the development of DL education. Although many courses have well-designed interaction, free courses, and optional paid certification, which enable students to learn DL courses online

without difficulty, these courses offer a little place for collaboration. It means that students learn and practice DL alone instead of studying as a group, which is very important for the development of modern DL.
Course contents need to be arranged in natural environments for DL practical education according to specific conditions, such as the differences of knowledge foundation, educational level, and professional direction. Even for college students of computer science majors, the DL course is difficult for them. Therefore, DL education needs to select and organize the course contents.

2.2. Dataset challenge

For training datasets, there have been many public datasets for DL of different purposes, such as MNIST (Deng, 2012), ImageNet (Deng et al., 2009), COCO (Lin et al., 2014), etc. However, we need to collect and mark datasets for our applications in many cases. Generally, good datasets are more critical than DL models for DL applications, and dataset marking is essential but tedious. However, many online DL courses use public datasets for experiments. In this case, learners do not know how to make their datasets for their application scenarios. Datasets making needs to solve the following problems. Firstly, we must collect interesting input data (e.g., images). We can collect the input data by a hand-made approach, but it takes a lot of time. Another commonly used way is to collect these data by crawling through the Internet. And the problem is that unwanted data may be crawled due to the uncertainty of network contents. Secondly, it is a vast project to organize and mark these collected data. There have been many ready-made marking tools, such as LabelMe, LabelImg etc. However, data marking needs lots of people and time, and hidden dangers of mislabeling exist, which may cause low accuracy of the DL model. In fact, task assignment for data marking is also a project problem, and there is a lack of a specific case for the student to referentially cooperate in data marking.

2.3. Computing challenge

The development of a neural network is consistent with the development of the computer. The growth of computing power promotes the increase in the size and complexity of neural networks. According to our test, training a simple LeNet5 model (5 layers) for MNIST digital recognition (Lecun et al., 1998) will take about one hour on Intel Core i5 CPU, and it takes only 90 seconds on Nvidia GTX 1080 GPU. But parallel computing device is too expensive for most commercial cloud servers are costly for undergraduates. They do not have adequate flexibility to be assigned to students. Colab is a cloud server platform of Google designed for DL and machine learning tasks. Colab is a cloud server platform of Google designed for DL and machine learning tasks, but such platforms may not be accessible in Chine due to the national policies.

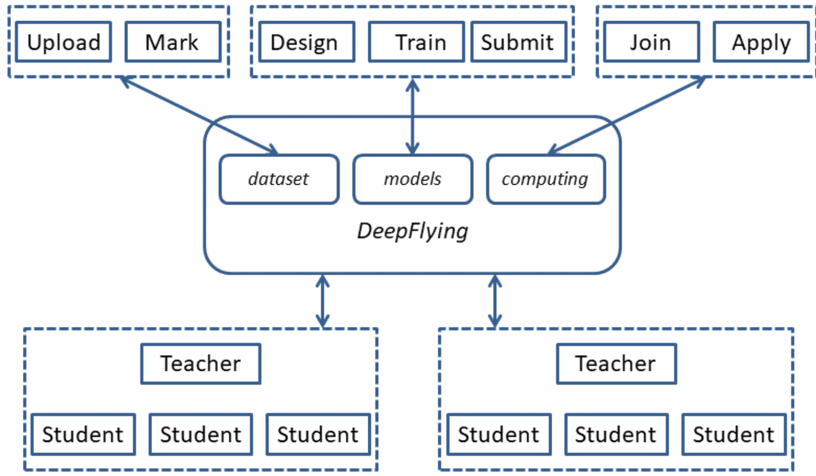
Moreover, one of the challenges is that in many universities with poor conditions (such as non-key universities), there is no condition to establish or purchase cloud service platforms for students. Generally, students have PC. And the DeepFlying (Deep learning and Flying apsaras) platform proposed in this paper has the advantage of centralizing and dispersing PC computing power to complete DL teaching practice. Therefore, the other choice is to buy components or cloud servers, which is very difficult for many students and poor universities (especially in Western China).

3. Addressing the common challenges

To address the challenges in practical DL education, we provide some solutions and test them in practice, as shown in Figure 1. In our DL course practice, we try on the Dunhuang theme. Therefore, we name our DL education platform DeepFlying, which utilizes collective intelligence to collect and share DL materials and resources. The shared resources mainly include datasets, DL models, and computation.

Teachers and students in different universities can access the DeepFlying platform to upload and mark data. Also, they can share their DL models on the DeepFlying platform and apply for computing resources for training DL models. Therefore, DL education materials, dataset making, and computing resources are essential for the DeepFlying platform.

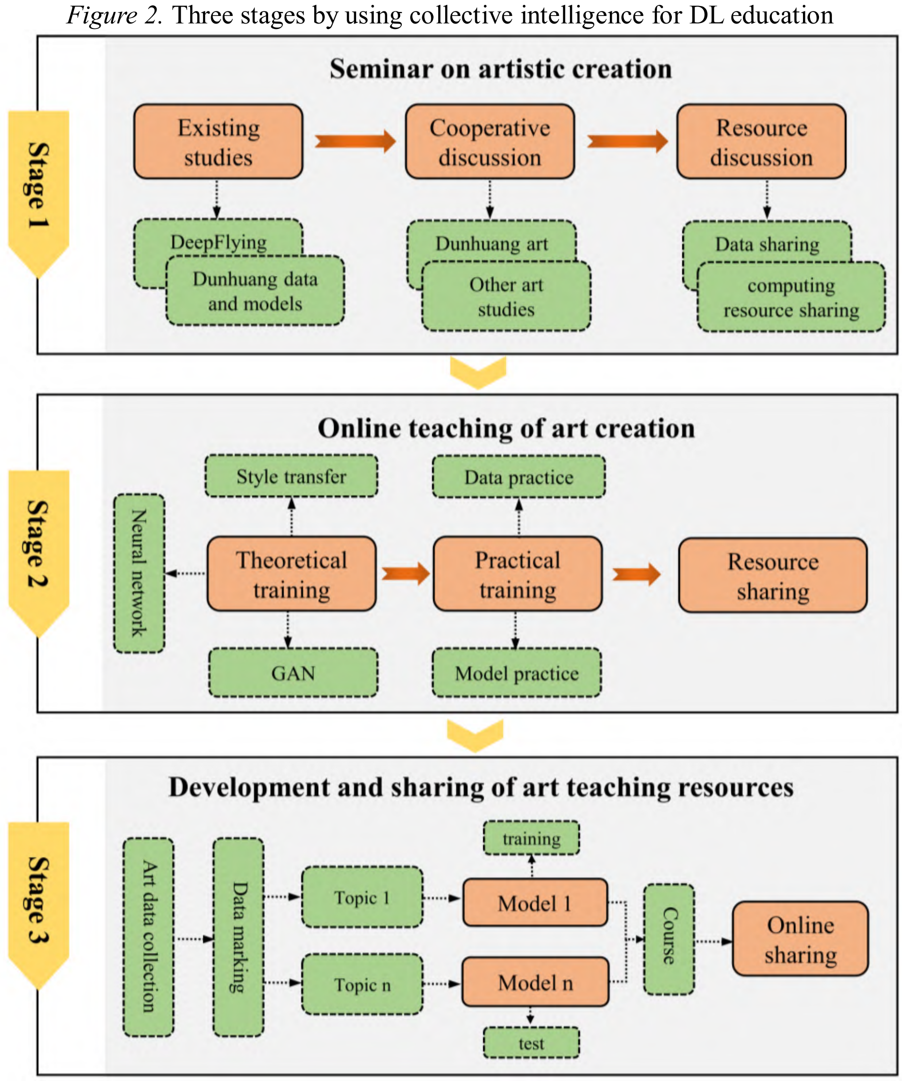
Figure 1. The schemes to address practical DL education challenges



3.1. DL education materials

To collect the ideas and teaching materials for DL education, we design a scheme based on the background of artistic creation. As shown in Figure 2, the process mainly consists of three stages. And the DL education is organized after these stages.

Figure 2. Three stages by using collective intelligence for DL education



3.1.1. Seminar on artistic creation

The first stage in the DL education is to hold a seminar on artistic creation. This seminar aims to identify topics and ideas for deep learning education among different universities. Existing studies such as the DeepFlying platform, Dunhuang dataset, and models are presented and discussed in the seminar. Next, more research ideas about this field will be put forward. These cooperative discussions may generate more teaching materials, including Dunhuang or other studies. At the end of the first phase, data and computing resource sharing methods are discussed.

3.1.2. Online teaching of art creation

The second stage in the DL education is to conduct online education on art creation. In this way, we can test the teaching materials and choose suitable teaching materials based on students' feedback. The online course includes theoretical training and practical training. In the theoretical training part, the theories of neural network (NN), style transfer neural network (STNN), and generative adversarial network (GAN) are introduced. Then, students are taught how to mark datasets, design, and train models in the practical training part. The marked dataset and trained models will be shared online.

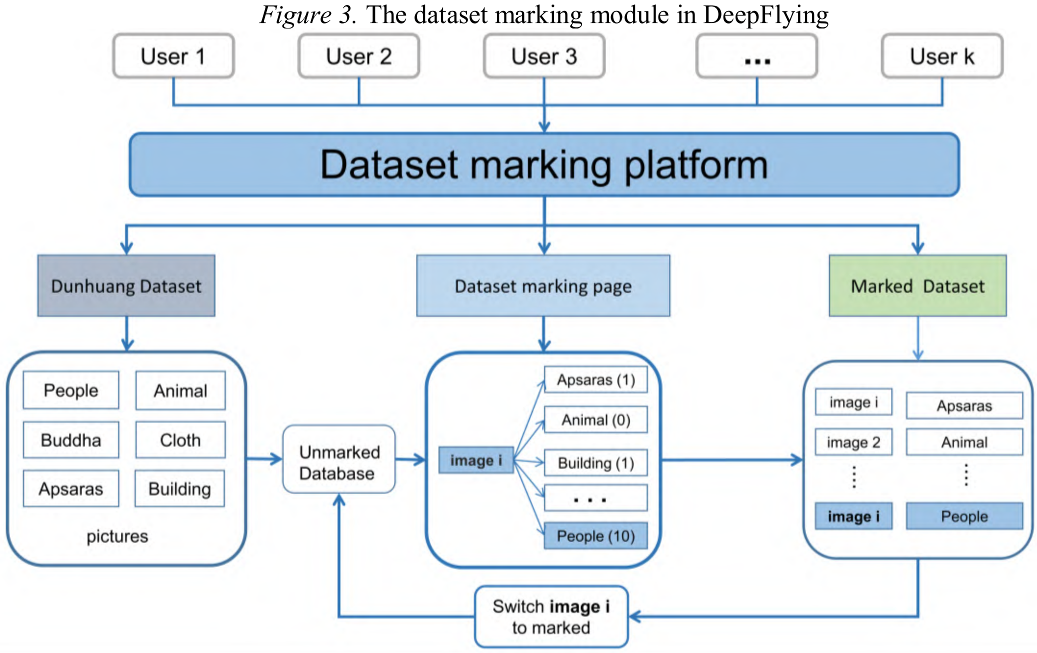
3.1.3. Development and sharing of art teaching resources

In stage 3, based on the experience of the first two stages, DL teaching on a specific artistic topic is conducted by different teachers. Students are taught to collect and share more art data in the course. Meanwhile, students finish data marking as their homework. Then, based on the open dataset, different DL topics are proposed and implemented by DL models. Students can team up to work on various DL tasks, such as each team focusing on a single classification function, and they are guided to train and test their models. At last, the materials, including data and models, are made into the open course and shared online.

3.2. Dataset making

Data collecting and marking are important for DL education. To enable students to collaborate in collecting and marking required datasets, we propose and design an online data collecting and marking module in the DeepFlying platform, denoted as dataset marking module, as shown in Figure 3.

Figure 3. The dataset marking module in DeepFlying



Each student needs to register as a user in the marking module, and students collect the dataset according to their homework. The dataset collection task is evenly assigned to students who attend the DL courses, and each student needs to collect and upload a portion of the dataset. Then, each student needs to register an account and mark parts of the dataset online, different from the data they collected. The marked data is randomly selected from the whole dataset. Each data is marked at least ten times, more trials would be applied if the most marked category has less count, and the top marked category is selected as the final category of the data. In this way, data will only be marked when students reach a consensus, preventing students from cheating when marking data or obtaining an unwanted error-marked dataset. Marked data will be stored in the marked dataset and removed from the unmarked dataset. In fact, with the development of the DL course, the dataset gets larger and larger. Meanwhile, more and more data are marked for training DL models.

In our DL course, Dunhuang data is used as a dataset for dataset making. The Dunhuang images include many types, such as People, Animal, Buddha, Cloth, Apsaras, and Building, etc., as shown in Figure 3. We have collected and marked nearly 60 thousand pictures in the DL course. In the future, more types of datasets can be made and shared through the platform.

3.3. Computing resources sharing

For the characteristic of large computational quantity, DL is difficult to be practiced in college education. For instance, training a ResNet50 (He et al., 2015) DL model for image recognition will take about 14 days on Nvidia M40 GPU, and it will take decades to train such a DL model on a regular computer without the help of GPU. Hence, we design a cloud-based computation resources sharing mechanism to provide a high-performance platform. There has been some could-based computation platform for DL model training. For example, Colab and Kaggle are online platforms released by Google, providing computation for machine learning and DL researchers. It is free for ordinary DL users and provides some application examples. However, both Colab and Kaggle limit training resources in a session. Colab offers 12 hours of training timing, and Kaggle delivers 9 hours of training timing, which leads to the use of these two platforms is not flexible enough for some time-consuming training tasks. Another problem is that both Colab and Kaggle are not available for Chinese students due to the national policy.

In our design, we assume that there are 40 students in a class. The shared computation server is configured with Intel Core i9-7900X CPU and four Nvidia GeForce RTX 2080Ti GPUs. Each student is assigned a Jupyter notebook account for DL model training. According to our test, the average performance of each account is stronger than Colab and Kaggle, and students completed their experiments with the help of our shared computation platform. We hope more education institutions join and share the computing resources.

3.4. DL models and transfer learning in DL course

In our DeepFlying platform, we provide DL models sharing mechanism to reuse trained DL models. One common way to solve the computation resource problem is the so-called transfer learning. Transfer learning is often used to reduce the computation based on previous trained DL models when training a DL model. Generally, to train a DL model of similar tasks that exist trained model, we do not need to train the DL model from scratch. The previously trained model can be used to initialize the weights of the DL model. According to the application scenarios, there are four types of transfer learning in DL, as shown in Table 1.

Table 1. Four application scenarios of transfer learning in DL

Sample sizes	Application similarity	Training method
Big	High	Fine tuning
Big	Low	Fine tuning or retraining
Small	High	Modify and train fully-connected layers
Small	Low	Redesign and retrain model

For instance, in the first case, the student can reuse an existing object recognition model by developing an object recognition application whose categories are commonly seen. They only need to download the weights file and load it into the DL model. Then, fine-tuning the DL model based on the new training dataset will achieve a good recognition model. This is the best condition for transfer learning.

In the second case, the new application dataset for training is large, lacking trained similar DL models. This condition mainly appears in specific applications, such as medical image diagnosis. In this case, we can still choose a similar DL model and execute a fine-tuning operation. If the newly trained model has a poor performance, we need to retrain the DL model based on the new dataset.

Another common scenario is that only a small dataset can be obtained, and there are already related DL applications. For instance, we need to develop a new face recognition application used to recognize 30 students. DL based face recognition approaches are widely researched and trained. In this case, the trained DL model of face recognition can be transplanted with modified fully-connected layers. Then, the face recognition model can be trained with the new dataset. In this process, the convolutional layers and pooling layers of trained DL already have feature extraction ability. Hence, the weights of convolutional layers are fixed, and the pooling layers have no weights. Only two or three fully-connected layers on the top need to be trained. It will significantly reduce the amount of computation of model training.

The final scenario of transfer learning is the worst condition, in which there is little training dataset, and there is no similar application model could be referenced. In this case, students need to redesign and train the DL model from scratch. In fact, it seldom occurs from the perspective of education because the dataset and model will accumulate gradually with the launching of the DL course. We can use transfer learning in DL courses and, first, roughly train a DL model with part of the training data before the DL course. Then students can utilize transfer learning and other training data to train and optimize the DL model. That is, we train a DL model as the base model, which is used to make transfer learning by students. The base DL model will be updated with the development of the course. In fact, transfer learning is an important learning approach used by people in the study. It provides a way for students to infer other things from one fact. The applications of transfer learning in DL education can be furtherly researched.

4. DL Course practice

To practice the collective intelligence idea and share learning mechanism for DL education, based on the DeepFlying platform, we start a short-term DL course practice in the summer, which aims to teach students DL technologies, including Convolutional Neural Network (CNN) (Jiang & Chi, 2019), Neural Style Transfer (NSF) (Gatys et al., 2016) and Generative Adversarial Networks (GAN) (Creswell et al., 2017). Based on these technologies, students need to make their artworks in groups.

4.1. Content of DL course

We assume that the students who take the DL course by default have a certain programming foundation, and they know how to program by Python programming language. However, the foundation of DL is unnecessary, and the DL course will be completed in five days.

The history of neural networks and DL will be introduced on the first day. And the disadvantages of neural networks in each stage are presented and discussed. Students are taught that computing power and large amounts of field training data are two critical factors for DL development. The Dunhuang datasets and shared computing resources in the DeepFlying platform are also introduced to students. Finally, students need to design and train a three-layer neural network for simple function fitting based on the TensorFlow DL library with the help of the DeepFlying platform.

The main course content of the second day is about CNN. CNN is the core technology of DL, which utilizes convolutional layers and pooling layers to extract features. Meanwhile, the weight-sharing mechanism of convolutional kernels can effectively reduce the number of weights to reduce the computational complexity of model training. Students need to know how the convolution and pooling operations are conducted today. Also, they need to understand the basic principles to design a DL model. As a simple example, students must implement a handwritten number recognition program based on DL and MNIST dataset (Deng, 2012).

On the third day, NSF and GAN models are introduced to the students. NSF is a type of transfer learning based on the trained DL model. The latest research on deep learning showed that different layers of the DL model could effectively extract features from different levels. Therefore, NSF can combine the features extracted from different images to transfer the style of one image to another. Trained DL models used to extract image features have been provided on the DeepFlying platform. Through NSF model practice, each group can generate their artworks.

On the fourth day, the teaching focal points of the GAN model consist of a Generator and a Discriminator. Students need to know that the Generator and the Discriminator are alternately trained until the Discriminator cannot judge whether the Generator generates the picture or not. Then, the Generator learned the statistical rules of trained images and could develop new artworks. Students can search the varieties of GAN to create their paintings.

4.2. Students attending DL course

We selected 40 students from universities to attend the DL course. These students are from 23 universities, and each university has no more than two students. Therefore, these students are in different educational environments. Four students are randomly selected and assigned into a group, and there are ten groups in total. At the beginning of the course, every group elects a leader by playing a game. These students were arranged to finish the DL course in groups, and each group needed to develop their DL artwork.

4.3. Dataset used in DL course

There is a little difficult when students build their own DL model using open-sourced DL packages, like TensorFlow, Caffe, and Torch. In the meantime, they can find many ready-to-go models on the Internet. However, it's challenging for students to perform DL model when they have limited data for some specific problem. Our course encouraged students to share in this situation, so we designed this dataset marking system as an instance.

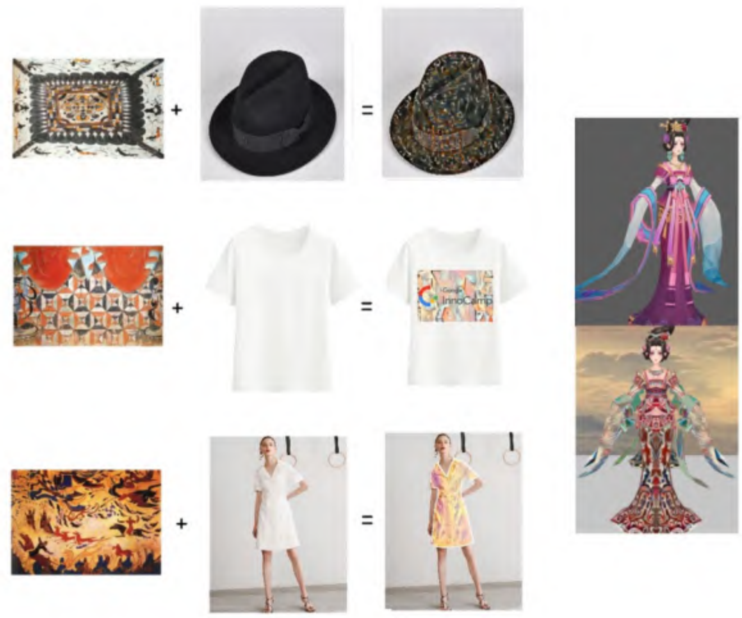
The dataset in the DL course is based on the Dunhuang frescoes images. Dunhuang murals are the representatives of ancient Chinese grotto murals. Although these murals have had a history of thousands of years, they have shown different styles in painting images and color forms. They utilized a small number of colors to paint pictures, which did not make people feel monotonous. In contrast, they show a unique gorgeous. Dunhuang frescoes reflect ancient Chinese culture and art style, which can be well used for today's art design reference. There are many Dunhuang frescoes images online. Students are arranged to crawl these Dunhuang images in groups. The crawled images are messy and need to be selected and sorted out. This is conducted on our dataset system. Students need to mark images online to finish their work. Dunhuang's mural images show different characteristics in the various dynasties. They can also be divided into different categories according to their contents, such as flying apsaras, landscape painting, Buddhistic stories, etc. Our DL course mainly focuses on the characteristic of colors and costumes, which can be used to conduct style transfer and costume generation tasks.

In addition, Dunhuang frescoes images are openly accessible by government-owned websites in China. However, the sites are designed to show art to the masses instead of providing data to DL research, so we crawled and marked the images to make Dunhuang data available to many DL learners.

4.4. Outputs of the DL course

After the theory course, each group is given two days to create their artwork based on NSF and GAN. In fact, students are entirely free to design their artworks. In this process, group leaders assign a task for each student. For example, some students are arranged to collect image materials, while others are engineered to debug or modify the DL code. Finally, each group must submit their artwork and their project document. Some artworks submitted by students are shown in Figure 4.

Figure 4. Some artworks submitted to the DL course



4.5. Evaluation of the artworks

We evaluated these artworks by group voting. Each group chooses a representative to evaluate the artwork of the other groups, and these representatives give scores between 0 and 100. The score results are shown in Table 2. We removed the maximum and minimum scores to get the final average scores of each group, and the top three groups were rewarded. Broke off both ends, the average scores fell in the interval 81 to 86, which shows that most groups learned about similar DL knowledge after the course. The top-ranked groups contain at least one amazing member expert who is good at coding or painting. For the students with lower performance, they need to struggle harder to finish their DL course. Finally, they can complete all courses and create an art piece with the help of their group, even if they have less prior knowledge.

Table 2. Evaluation results of student artworks

Judge/Group	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
J1		77	86	70	90	89	89	83	87	65
J2	88		76	77	75	74	78	75	76	73
J3	100	78		86	88	74	84	84	84	67
J4	98	83	89		87	95	84	80	82	82
J5	99	87	91	92		93	94	92	88	85
J6	94	87	86	92	88		88	87	85	85
J7	95	76	80	82	78	82		80	77	67
J8	92	73	77	78	84	82	85		70	65
J9	90	83	84	79	83	83	85	80		69
J10	95	88	85	89	87	89	86	86	85	
Highest	100	88	91	92	90	95	94	92	88	85
Lowest	88	73	76	77	75	74	78	75	70	65
Total	851	732	754	745	760	761	773	747	734	658
Average	94.71	81.57	83.36	82.29	85.0	84.57	85.86	82.86	82.29	72.57
Rank	1	9	5	7	3	4	2	6	8	10

4.6. Evaluation of the DL course

Two weeks after the DL course, we collected the student opinions by answering the survey online. Finally, 39 questionnaires were obtained (One student did not reply). The main contents of the questionnaire include the evaluation scores of many course items, including registration process evaluation, reception service evaluation, teaching method evaluation, project content evaluation, and accommodations evaluation. The total score of each evaluation is 5. And the statistical results, including total, average scores, and standard deviation of scores, are shown in Table 3.

Table 3. Course evaluation results based on survey online

Score	Total	Average	Std
Registration	188	4.821	0.4456
Reception	192	4.923	0.2664
Teaching method	193	4.948	0.2206
Project content	185	4.743	0.5869
Accommodations	190	4.871	0.3343

In this table, total scores, average scores and the standard deviation of each item are listed. Overall, the evaluation of the DL course is good. And the teaching method got the highest score, which indicates that this teaching method is acceptable for college students, even in a few days.

5. Discussion and conclusions

DL has been the core technology of AI. However, practical DL education needs to solve the course materials, dataset, and computing problems. Therefore, how to promote DL education in college is still a problem due to the complexity of DL course practice. In this article, we proposed the collective intelligence idea for DL materials. Three stages are designed before DL education. Meanwhile, a DeepFlying platform and the resource sharing mechanism to solve data and computation problems are developed. Training datasets are collected and marked by students based on the DeepFlying platform. Some previous trained DL models and computation resources are also provided and shared on the platform.

To test the effect of DL education, we make a short summer school practice. Forty college students are selected to attend the DL course. The course theme mainly focuses on Dunhuang mural pictures. Students are required to collect and classify part of Dunhuang images to put datasets marking into practice, which can also help the platform collect more shared datasets. The contents of the practical DL course mainly include the principles and practice of neural networks, NSF, and GAN. Students submitted their artworks made on the DeepFlying platform according to what they learned in the DL class. Evaluations of the artworks and course are also collected. The results show that students can learn DL contents and finish their artworks well. Meanwhile, they also have a high evaluation for the DL teaching method.

In this paper, we mainly focus on DL education for college students. And the course content is limited to classical CNN-based deep neural network models, which are determined by the background of Dunhuang art. Other deep models, such as long short-term memory (LSTM), can be introduced in the DL course. But it needs more application scenarios and course design. In the future, more applications can be developed for the DL course. In this way, the platform will collect more shared datasets for DL education.

Statements on open data, ethics and conflict of interest

A request to access data can be directed to authors. The research performed in this work is the sole work of the named authors. The ideas presented in this article do not pose any risks to individuals or institutions. We declare that we do not have any conflicts of interest regarding the study.

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